Interpretation of soil quality indicators for land suitability assessment – A multivariate approach for Central European arable soils

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Abstract

Soils and their functions are critical to ensure the provision of various ecosystem services. Many authors nevertheless argue that there are a lack of satisfactory operational methods for quantifying the contributions of soils to the supply of ecosystem services. Therefore, it is difficult to automate and standardize the mathematical and statistical methods for the selection of indicators and their scoring. Our objective is the development of a novel soil quality and ecological indicator selection and scoring method based on a database representing the most common Hungarian soils typical for arable lands of Central Europe (Chernozems, Phaeozems, Luvisols, Cambisols, Gleysols, Solonetz, Arenosols). For evaluation purposes, soil texture, depth to groundwater table, soil organic matter (SOM), pH, calcium carbonate equivalent (CCE), electrical conductivity (EC), Na, available N, P, K, Mg, S, Cu, Zn and Mn of 1045 plots representing a total land area of about 5,000 hectares at 0-30 cm layer were analyzed. We classified the samples into 25 soil types. Using correlation, principal component analysis and discriminant analysis the direction and strength of the intercorrelation of indicators and their combinations were determined. Indicators were classified into the following categories: (1) indicators that characterize nutrient retention and cation exchange capacity: texture, SOM, EC and Na; (2) available nutrients, relatively independent from management practices: K, Mg, Cu; (3) indicators that determine base saturation: pH, CCE, available Mn; (4) highly variable available nutrients: N, S, P, Zn. By reviewing the results of Hungarian long-term experiments, we interpreted the soil indicators as a function of agricultural suitability. Following the parameterized and non-linear interpretation of the indicators, we analysed the variance of soils, in terms of their agricultural land suitability. According to the intercorrelation of input indicators and variance of scored indicators the minimum data set for soil quality assessment includes texture, depth of groundwater table, SOM, pH, Na, available K, P and Zn. In order to further advance our soil quality assessment model, our following goals target the determination the hierarchical ranking and grouping of soil parameters in a combined manner.

Keywords: indicator scoring functions, principal component analysis, soil quality index, available nutrients, soil moisture regime

1. Introduction

To prevent and mitigate soil degradation processes, spatial and temporal heterogeneity pedological data with readily measurable indicators, are essential for appropriate soil management strategies. Soil quality refers to the capacity of soils to function and sustain plant and animal life within natural and managed environments (Karlen et al., 1997). Soil quality cannot be directly obtained but rather inferred by measuring the appropriate soil physical, chemical and biological indicators (de Paul Odabe and Lal, 2016).

Soil Quality Indices (SQIs) synthesize soil attributes into a format that enhances the understanding of soil processes and promotes appropriate management. The Soil Management Assessment Framework (SMAF) is an example of an SQI that operates in three steps (Andrews et al., 2004): (1) indicator selection; (2) interpretation of the selected indicators (scoring); and (3) aggregation of indicators in an index through weighted additive technique. Site-specific adaptations of these SQI are the most commonly used approaches today to evaluate impacts of agricultural practices, cropping systems (Armenise et al., 2013; Li et al., 2013; Ivezić et al., 2015; Raiesi and Kabiri, 2016; Biswas et al., 2017), land use change and land degradation (Masto et al., 2016; Raiesi, 2017). During a land suitability assessment (Kurtener and Badenko, 2000; Baja et al., 2007), the most important task is the evaluation of the productivity function of soils and the impact of soil properties on yield. However, this is complicated as soil properties, in various combination and to a different degree, influence crop yields and determine soil functions in a mixed manner.

Among the available soil quality indicators selection methods, Total Data Set (TDS) and Minimum Data Set (MDS) have been commonly used (Ghaemi et al., 2014; Rojas et al., 2016). In the MDS indicators are selected based on expert opinion or multivariate statistical analyses, most commonly through principal component analysis (PCA) (Andrews et al., 2004).

The second step is normalizing the MDS indicators by different numerical scales (usually between 0 and 1) using linear and non-linear scoring functions. The mathematical basis of this scheme is provided by the Fuzzy logic (Zhang et al., 2004; Busscher et al., 2007). This method is a clustering approach in which the true values of variables (membership) may be any real number between 0 and 1, where, in our case, 0 completely fails to fulfil, while 1 completely fulfils the demands of land use. Globally, the most commonly accepted linear and non-linear functions and integrating method of scaled indicators with a weighted additive manner provided by the SMAF (Andrews et al., 2004). In some cases, the selection, the linear interpretation, and determination of scoring thresholds of the indicators are based on linear correlation between the indicators and yield (Thuithaisong et al., 2011; de Paul Obade and Lal, 2016; Biswas et al., 2017).

The need for the standardization of indices is a vital issue (de Paul Obade and Lal, 2016). We believe that the automation of the statistical selection of MDS is insufficient as the impact of selected soil parameters for the ecological functions is usually non-linear. Evidently, the functions of soils and soil quality are manifested under given conditions (climatic, hydrologic and topographic), and can only be interpreted according to land use type or the specific necessities of the plant grown in a specific soil. When selecting indicators soil quality indexes should be meet the needs of a variety of soil types even in relatively small areas (Juhos et al., 2015).

There is a limited number of Central European SQI references available (Ivezic et al., 2015; Teodor et al., 2018). In Hungary, soil quality indices based on simple indicators, are not in use for land evaluation (Makó et al., 2007; Debreczeniné et al., 2003; Tóth et al., 2007a). The adaptation of soil quality indices to different environmental conditions is influenced by the employed soil analytical methods. In our opinion, the development of soil quality indices, especially for land suitability assessment, under the temperate climate of Central Europe requires a more complex multivariate approach.

Our objective, therefore, is the development of a novel soil quality assessment method based on a database representing some Central European cultivated soil types and Hungarian soil analytical methods. We intend to elaborate a multivariate soil evaluation method, which expresses the rate, quality and combination of the limiting factors on soil productivity. Our specific goals in this study included (1) the multivariate assessment of indicators determined according to the existing Hungarian standards (2) the determination of the direction and strength of their intercorrelation and (3) the comprehensive evaluation of the indicators by mathematical modelling and according to the scored indicators by soil types identification of limiting factors for plant growth. These goals were achieved by reviewing the results of Hungarian long-term experiments, the complex and mutual interpretation of the indicators by mathematical modelling as a function of agricultural land suitability.

2. Materials and methods

2.1. Site description

The employed soil database, representative of Hungary's farmlands, was compiled from the laboratory analyses of 1045 soil samples collected from a total land area of about 5,000 hectares. Each soil sample represents a homogeneous land parcel of maximum of 5 hectares. In all cases, samples were taken from a depth of 0 to 30 cm. The geographical location of the sampling sites is shown in *Figure 1*. The soil types of the research sites and their qualifiers are shown in *Table 1* according to the World Reference Base (WRB) (FAO, 2014) classification. The climate of the studied sites is characterized by cool winters and hot, dry, drought-prone summers, with a mean annual precipitation of 580 mm and mean annual temperature of 10.5°C (Fábián and Matyasovszky, 2010). Each of the experimental sites is uniformly cultivated by conventional tillage techniques. The following crops have been grown in a crop rotation: winter wheat (*Triticum aestivum* L.) and maize (*Zea mays* L.), and occasionally alfalfa (*Medicago sativa* L.), sunflower (*Helianthus annuus* L.) and rape (*Brassica napus* L.).

2.2. Soil analyses

The total analysed soil data set is composed of parameters determined according to the responsible authorities. Soil pH was determined at a soil/1 M KCl solution ratio of 1:2.5 and electrical conductivity (EC) was measured in a 1:5 soil/water mixture potentiometrically (MSZ-08-0206-2:1978). Determination of the calcium carbonate equivalent (CCE) was conducted using the volumetric method (MSZ-08-0206-2:1978). Soil organic matter (SOM) was measured by the Tyurin method (Kononova, 1966). Available nutrient contents were determined with acidic (pH 3.75) ammonium lactate extraction (Egnér et al., 1960) for phosphorus (P) and potassium (K), in 1 M KCl extraction for nitrogen (N), magnesium (Mg) and sulfur (S), in nKCl + EDTA extraction (MSZ 20135:1999) for zinc (Zn), copper (Cu) and manganese (Mn). The determination of soluble and exchangeable sodium (Na) was based on extraction with acid ammonium lactate (Egnér et al., 1960). Soil texture was characterized using a plasticity test by the water volume (cm^3) for consistency change to fluid for 100 g of soil (MSZ-08-0205:1978). This water volume highly correlates with the clay content and the exchangeable Na, and it well characterizes the water retention capacity of soils (Várallyay, 2008). We also monitored the mean annual groundwater table depths for Solonetz soils and Gleysols at multiple sites.

2.3. Statistical analyses

The paired relation between the variables was examined by the Pearson correlation coefficient (r). To determine intercorrelation among the indicators, we also performed a Principal Component Analysis (PCA) based on the standardized database. For standardization, we used the formulae log(x+1) in order to enhance normality and linearity and to reduce the effect of outliers. The suitability of the sampling (selected variables) was determined with Kaiser-Meyer-Olkin (KMO) and Bartlett tests. Only principal components (PCs) with eigenvalue > 1.0 were analysed (Andrews et al., 2004). The PCs were evaluated based on the loadings of the individual variables (the correlation between the variable and the principal component). To determine the explanatory power of the soil forming processes of input indicators, for the WRB orders as dependent category variable, discriminant analysis (DA) was performed with the PCs as independent variables. Normality of data was analysed by the Kolmogorov-Smirnov test and skewness and kurtosis of variables. All data were statistically processed using *IBM SPSS Statistics 22* and *MS Excel*.

2.4. Indicator scoring and mathematical modelling

To develop novel site-specific soil indicator scoring functions, we analysed the results of the Hungarian fertilization and soil amendment long-term experiments and land management methods (*Table 2*). According to our findings, the indicators and their critical threshold values were analysed and interpreted. By reviewing the literature, we also incorporated the ecological requirements of the crops but we did not evaluate indicators plant-specifically. Practically, however, crop rotation is employed, therefore, a general evaluation was applied to the most common crop cultures. All indicators were scored on a scale of 0 to 1 expressed either on the linear or non-linear scale, where 0 completely contradicts the demands of land use, while 1 completely corresponds with that. As individual parameters cannot be evaluated independently, we took into consideration the soil properties most directly influences each other, i.e. the models were differentiated by soil categories in some cases. The models of soil quality properties and their parameters are shown in *Table 3*. The mathematical modelling was performed in *MS Excel* software.

The pH was interpreted with a bilogistic model that has a saturation value (p0) with slope and inflexion parameters in both the increasing (p1, p2) and decreasing phases (p3, p4). Asymmetric saturation and degradation models were used to score the texture properties. Based on the groundwater depth their increasing and decreasing slope parameters (p1, p2) and axis shift and peak point parameters (p3, p4) were changed. The EC and Na were interpreted using logistic models ("less is better") where p0, p1, p2, p3 are their limit, slope and inflexion point parameters, respectively. The logistic models ("more is better") of the available K and P are significantly influenced by soil texture and pH hence their parameters were changed accordingly. The SOM, available Mg, Zn and Cu were interpreted with saturation models (where p1 is the saturation parameter, p2 is the slope parameter) but when modelling we made a difference by soil texture. In the case of the saturation model of available Mn, the parameters of function were differentiated by soil pH. The mineralized N and S contents were linearly ranked („more is better") using the formulae $y = x/x_{max}$ where x_{max} is the maximum value in the database.

3. Results

3.1. Bivariate correlations between soil quality indicators

The descriptive statistics and the linear correlation matrix of the pedological indicators are shown in *Table 4* and *Table 5*, respectively. On the analysed database a strong correlation (r>0.8) was found between pH and the CCE indicators, while the influence of base saturation was clearly observable on both parameters., a significant, but weak (r<0.39) or moderate (r=0.40-0.59) correlation exists among pH, Na and EC since salt accumulation and Na adsorption do not always occur together. In addition, the depth of $CaCO_3$ accumulation zone also indicated a great variability among the studied soils. Only a few Solonchak soils were found in the analysed database and in general, this soil type is rarely cultivated and used as farmland. EC strongly correlated with available Mg and S, therefore, besides Na, Mg and S must also be present among the water-soluble salts. Although Na did not indicate exchangeable sodium percentage (ESP), the physical impact of Na-saturated colloids on water retention and drainage properties of soils is well represented in the texture indicator based on consistency change. A weak but significant linear correlation was observed between Na and soil texture. SOM showed a moderate correlation with texture. In the analyzed dataset, available Mg and Cu indicated a high correlation with texture, while only a weak and moderate correlation was found between available K, N, S and Zn and texture. Consequently, these nutrients are adsorbed most commonly to the mineral colloids of soils. Among the available nutrients, Cu, Mn and P showed the highest but only weak-moderate correlation with soil pH.

3.2. Multivariate statistical analyses

According to the eigenvalues greater than 1, the PCA yielded four principal components (PCs) explaining a total of 75.658% of the variance for the entire set of variables (*Table 6*). The commonality of the variables, which expresses the rate of preserved heterogeneity of the given parameter, were larger than 0.588. The particle size distribution and the influenced properties by texture are expressed in PC1 based on the larger loading value of texture, Mg, Cu, EC, SOM, K and Na. PC1 explains 33.55% of the total variance of the input indicators. The second factor accounted for 22.044% of the total variance. PC2 was considered as a specific chemical parameter due to the high loadings of the Mn and CCE and pH indicators. Available P and Zn indicator loading values were the largest in PC3. The variance reached 10.931% in the latter case. The PC4 accounted for 9.134% of the total variance. PC4 was labelled as available nitrogen and sulphur due to the high loadings of the N and S indicators.

The linear discriminant analysis was carried out for the WRB classification at the values of PC1, PC2, PC3 and PC4 as independent variables. Our results indicated a prediction accuracy of only 47.5% for the four principal components of the WRB categories. The canonical correlation analyses showed that the first and second discriminant functions (DFs) explain 70.9% and 27.1% variance of the independent variables, respectively, i.e. they almost completely account for the total variance. According to the values of the structure matrix, the ranking order of the principal components is PC1 (0.709), PC2 (-0.497), PC4 (0.100) and PC3 (0.089) in DF1, whereas PC2 (0.792), PC1 (0.542), PC3 (0.354) and PC4 (-0.022) in DF2. Soil types primarily differentiated as a function of PC1 and PC2 values indicating the physical and chemical properties of soils (*Fig 2*). At the same time, the influence of PC3 and PC4 proved to be less important.

3.3. Scored indicators

The statistics of the scored indicators is shown in *Table 7*, whereas the mean values according to the soil types are presented in *Table 8.* The distribution of the obtained y_pH values was skewed left significantly due to the higher frequency of acidic values in the database. The lowest y_pH values are usually found for dystric Gleysols and dystric fluvic Arenosols (No 11, 16, 20, 23). The distribution of interpreted Na and EC variables are markedly skewed to the left. The y_EC value was found relatively low for Solonetz and sodic Gleysols. The mean y_Na value was between 0.28 and 0.67 for the latter soil types (No 21-25).

Due to their extremely high spatial variability in terms of texture and location, the studied soils of Hungary showed a relatively high standard deviation of y_texture values. The lowest values were obtained for reductigleyic and clayic Gleysols soils (No 7 and 8) with a mean value of 0.32 to 0.37. The mean y_texture value was between 0.57 and 0.68 for arenic Cambisols és Arenosols (No 17-20).

The mean value of y_SOM for the entire database was 0.69 with a normal (Gaussian) distribution. Values of less than 0.6 were typical for some Gleysols and Solonetz soils due to their high clay contents and anaerobic conditions (No 8, 10, 15, 16, 22, 23). Values below 0.6 were also found for Arenosols owing to their low SOM content and loose structure with large pore spaces (No 20). Scored values between 0.6 and 0.7 were common for Phaeozems, Cambisols and Luvisols formed under dense forest canopies, where soils are characterized by reduced organic matter and humus accumulation. Unsurprisingly, the highest y_SOM values were found in Chernozem soils (No 1 and 3).

Among the interpreted parameters, the y_N and y_S parameters have the largest variance, and unlike the other factors, they are skewed to the right and consequently their mean scored values are extremely low (0.13 and 0.08). The highest scored values of y_S were characteristic for the saline and sodic soils (No 22 and 23), thus this parameter indicates the accumulation of water-soluble salts.

Compared with other nutrients, the mean of the scored values of y_P (0.56) is the lowest in the entire database, indicating lowered and depleted phosphorous availability (and lowered release rates) in the studied soils. The phosphorus imbalance and deficiency (low dissolution and mineralization rates) in the soil may have been caused by insufficient fertilization practices or extreme pH conditions.

Based on the y_K and y_Mg values, potassium imbalance and deficiency likely occurs in the studied soils, as low potassium availability and concentration may be observed in many different soil types (e.g. No 5, 6, 11, 16, 20). The magnesium-supplying and releasing capacity of the analysed soils is generally high, with a mean scored value of y_Mg (0.98) and a standard deviation of 0.058. The lowest y_Mg values were found for Arenosols due to the highest ratio of nutrient loss by leaching, low surface charge density and the reduced specific surface area of colloids.

The average values and the standard deviation values of y_Mn were similar to the corresponding parameters of magnesium. Lower values were commonly found a reducigleyic dystric Gleysols and acidic soils of sandy textures (No 7, 18, 20). Based on the values of the interpreted variables, we learned that the Cu-supplying capacity of the studied soils is generally good, with scored values less than y_Cu <0.8 only found in a very few soil samples. In accord with phosphorous, low Zn-supplying capacity characterizes each analysed soil type, and y_Zn ranged widely between 0.144 and 1.000 with a mean value of 0.64.

4. Discussion

4.1. Indicators used for soil quality indices

To estimate the impact of soil chemical properties on nutrient cycle as well as water and nutrient uptake, most authors studied pH-H_2O (occasionally pH-$CaCl_2$), electrical conductivity, cation exchange capacity (CEC) and exchangeable cations (Zhang et al., 2004; Qi et al., 2009; Masto et al., 2015). Under arid climates, exchangeable sodium percentage (ESP), sodium adsorption ration (SAR) and calcium carbonate equivalent (CCE) complete the list of analysed parameters. Nevertheless, due to the correlation of the above-listed parameters, only one or two indicators have been selected and used in the development of soil quality indices. From the results of multivariate statistical analyses, it is claimed that under typical soil conditions in Hungary, pH, CCE, EC and AL-soluble Na were found to be suitable indicators of soil quality.

Among the indicators that characterize the physical properties of soils, available water retention capacity, bulk density, aggregate size distribution and stability (especially the mean weight diameter) and the particle size distribution (clay, silt and sand percentage) have been extensively studied by former studies (Ghaemi et al., 2014; Rabbi et al., 2014; Göndöcs et al., 2015; Raiesi, 2017). In our assessments, due to its impact on soil water and air dynamics, soil texture, as a physical parameter, was preferably implemented during the elaboration of the evaluation algorithm. Under the drought-prone climatic conditions of Hungary, water retention capacity of soils profoundly influences the yield of dryland crops (Farkas et al., 2005; Tóth et al., 2007).

The organic matter dynamics of soils influences both their nutrient cycle rate and the functional activity of soil biota (Greiner et al., 2017; Fekete et al., 2017). To characterize this ecosystem function, many indicators have been applied. Among them, soil organic matter, carbon content (SOM/SOC or TC) have been used the most commonly (Yao et al., 2014; Nakajima et al. 2015; Biswas et al. 2017; Nabiollahi et al. 2017). Biological indicators allow the detection of the impacts of management practices and different crops as they are not limited to specific influences (e.g. Karlen et al., 1997; Lima et al., 2012; Zobeck et al., 2014; Raiesi and Kabiri 2016).

Chemical and physical properties also impact soil organisms and consequently, biological indicators would be distinct indicators for the identification of soils in this study (Matics and Biro, 2015; Dudás et al. 2017). Nevertheless, we did not employ this approach as a comprehensive database on the biological activity of soils is not available in Hungary. Furthermore, our database was based on the farmlands of similar cultivation and land use management practices and our primary goal was to interpret the most basic physical and chemical parameters. After validation, it would be the incorporation of biological parameters into the evaluation would considerably improve assessment accuracy.

Comparison of available and soluble nutrient contents, measured with different extracting solutions, is often difficult, as their comparison and data usability are influenced by the physical and chemical properties of the studied soils. For the determination of available phosphorous, the most commonly used extraction solution is the 0.5 M $NaHCO_2$ (pH 8.5) (Armenise et al., 2013; Li et al., 2013). In contrast, in Hungary the acidic ammonium lactate (pH 3.7) method is used, which dissolves the less available Ca- and Mg-phosphates of alkaline soils (Buzás et al., 1979; Ivezic et al., 2015). Therefore, it is indispensable to include the chemical properties of soils in the evaluation algorithms. Some authors used ammonium-acetate-soluble potassium content (Sharma et al. 2014; Singh et al. 2014; Yao et al. 2014), which is more in line with the latest Hungarian datasets. Available magnesium is rarely analysed in soil quality studies and is only interpreted by a few authors (Saglam et al., 2015; Sharma et al., 2014). DTPH-extractable Fe, Mn, Cu and Zn were interpreted by some authors (Lima et al., 2012; Ramachandran et al., 2016; Biswas et al., 2017). In Hungary, available sulphur and magnesium were determined with 1 M KCl solution and metallic micronutrients were measured using EDTA +1 M KCl extraction (Buzás et al., 1979). This extraction method enables only a limited comparison with similar parameters published in the international literature.

4.2. Multivariate statistical methods for selecting and weighting soil quality indicators

Based on the literature review, it can be stated that the selection of MDS indicators is automated using principal component analysis (PCA) (Zobeck et al., Nakajima et al., 2015; de Paul Obade and Lal, 2016; Nabiollahi et al., 2017). PCA generates the linear combination of input parameters, namely principal components (PCs) that do not intercorrelate. By using PCA results (eigenvalues of PCs and loadings), indicators, characterized by low intercorrelation, can be selected, in our case, these are the texture, K, Na, CCE, Mn, P, Zn, N and S (Table 6). These indicators explain the majority of TDS variance and the results of the PCA are also used to weight the indicators for calculation the soil quality indices (Andrews et al., 2004). Nevertheless, the question may arise whether the variables of the highest variance are at the same time the most important? Following our variance analyses of the parameterized and non-linear interpretation of the indicators, in terms of their agricultural land suitability, we may ponder whether the MDS variables should be selected before or after the scoring.

In our opinion, the complex interpretation of the principal components (PCs) is more vital regarding their information source on the latent relationship among the individual indicators, including soil forming processes and the impacts of land use (Juhos et al., 2015; Raiesi and Kabiri, 2016; Vinhal-Freitas et al., 2017). PC1 specifies the amount of mineral and organic colloids, and consequently, the cation adsorption capacity of the soil. Eventually and indirectly, it identifies the relative maturity level of soils, water and nutrient retention capacity which subsequently determines soil fertility and productivity (Makó et al., 2003; 2007; Rajkai et al., 2015). Indicators that specify the process of salinization and sodification are not separated in the PCA. The PC2 shows that acidity and alkalinity very strongly controlled by the $CaCO_3$ content of the analysed soils (Csathó, 2001). Accumulation of Na-salts is not significantly expressed by pH measured in KCl solution. Mn availability and solubility are also influenced by $CaCO_3$ content, as pronounced negative linear correlation exists between these two parameters (Buzás, 1979). The significant correlation between the available P and Zn indicators and their segregation in the PC3 are explained by multiple factors. Zinc is strongly adsorbed on the surface of clay minerals and has a low concentration in the soil solution. The solubility of various Zn-salts is low and increases with decreasing pH (Fomina et al., 2010). In soils of high phosphate concentration, Zn-phosphates of low solubility are formed, which can be detected by standard extracting solutions. According to PC4, the elements N and S have similar biogeochemical cycles and the concentration of their mineral forms rapidly changes in the soil.

According to the significant predictive power of the PC1 and PC2 in discriminant functions, it can be stated that the zonal, climate-determined soil types, like Luvisols and Chernozems, are easily identified based on their chemical properties, while Arenosols and sandy Cambisols are recognized according to their physical (textural) attributes (Makó et al., 2007). *Figure 2* reveals the diverse character of Gleysols and the variable depth of $CaCO_3$-rich and natric horizons of Solonetz soils. Our results pointed out the common prediction power of the texture, SOM, K, Mg, Na, Cu, EC, CCE, pH and Mn by soil genetic types and the active soil forming processes.

We propose that the pedological indicators can be classified into four major groups. (1) Water balance and salt dynamics indicators that characterize nutrient retention and cation exchange capacity of soils: texture, SOM, EC and Na. (2) Nutrients, relatively independent from and management practices and associated with and adsorbed on the surface of soil colloids and clay minerals: K, Mg, Cu (3) Indicators that determine base saturation and available nutrients, where nutrient availability is primarily determined by the base saturation of soils: pH, CCE, Mn (4) Highly variable nutrients and/or nutrients greatly influenced by climate and type of land management. Available nutrient concentrations of N, S, P, Zn, however, are primarily influenced by fertilizer application intensity. Consequently, the critical evaluation of the PCs and indices according to soil types may prove useful in multiple analytical algorithms (Mukherjee and Lal, 2014; de Paul Obade and Lal, 2016; Biswas et al., 2017).

4.3. Indicator scoring functions

We believe that the individual environmental and soil parameters cannot be evaluated independently. Furthermore, the functions of soils and soil quality are revealed under given conditions and can only be interpreted specifically according to land use type or the exact necessities of the plant grown under the given environmental conditions. In contrast, based on former literature, it is often necessary to use and adapt individually analyzed indicators and scoring functions from other studies conducted under different ecological conditions. The most common indicator scoring functions in the literature are summarized in *Table 9*.

We believe that the linear interpretation of indicator scoring thresholds is based on the linear correlation between the indicators and yield. However, this correlation only proved successful for certain a limited number of soil types, where only one or two soil parameters limit yield and soil productivity (Thuithaisong et al., 2011; de Paul Obade and Lal, 2016; Biswas et al., 2017). In addition, the soil quality-yield relation is not necessarily linear, while other soil parameters explain yield in a given combination (Cox et al., 2003; Ayoubi et al., 2009; Juhos et al., 2015).

The scored pH values (y_pH) indicate that the crops favoured the high base saturation in soils and they were less sensitive to acidity than to high alkalinity (Csathó, 2001; Debreczeniné and Németh, 2009; Nagy, 2011). Therefore, pH-KCl values of 5.5 to 7.5 were considered non-limiting, which corresponds to the scored values of y = 0.9 to 1.0. Any pH value below 4.5 and above 8.0 were evaluated as strongly limiting values for crop growth, therefore scored values of lower than 0.5 were assigned to them. Many crops are commonly unresponsive to high $CaCO_3$ concentration, therefore CCE was not interpreted separately. CCE is an important indicator in terms of nutrient availability and solubility, hence it was evaluated and included in the statistical analyses during nutrient dynamics evaluations.

The interpreted EC and Na values point out the moderate tolerance of crops against salinity and high sodium contents and the unfavourable impact of adsorbed Na on soil aeration and hydraulic and physical properties (Prettenhoffer, 1969; Szabolcs, 1971). All investigated crops poorly tolerated high salinity and excess concentration of alkaline Na-salts. This property was already partially included in the evaluation of pH. EC values of <0.4 dS m^{-1} and Na values <75 mg kg^{-1} were assumed non-limiting for crop growth (where y>0.9), whereas EC higher than 0.8 dS m^{-1} and Na values exceeding 200 mg kg^{-1} were assumed critical for crop growth, corresponding to y values of less than 0.5.

In terms of the soil physical characterization, our analyses focused on the water retention potentials of soils and soil aeration; i.e. parameters primarily determined by texture and the depths of the capillary fringe zone and the groundwater table (Makó et al., 2003; Farkas et al., 2005; Tóth et al., 2007; Tóth et al., 2014; Rajkai et al., 2015). Whereas higher water retention capacities correspond to better moisture availability during periods of drought, rainy periods enhance the development of reductive and anoxic soil conditions. Our mathematical model shows that the highest available water capacity exists for loamy, and clayey loam soils (Várallyay, 2008; Rajkai et al., 2004). Furthermore, the higher the clay content of the soils is the deeper is located the optimal depth of the groundwater table (between 85 and 180 cm) (Géczy, 1968; Lóczy and Dezső, 2013; Lóczy et al. 2017). Our model was poorly applicable for alfalfa due to its preference for deep groundwater table.

When interpreting SOM, the biological functions (nitrogen-supply, water retention and soil structure) of organic matter was evaluated (Greiner et al., 2017). Since the mineralization and release of nitrogen is primarily the function of air and water availability and textural properties under the given climate (Fekete et al., 2017), the same SOM content provides better conditions for sandy loam soils than clayey soils (Buzás et al., 1979; Debreczeniné and Németh, 2009). SOM, through its influence on nitrogen-supply, water retention and soil structure, significantly affects yield in Hungary (Debreczeniné and Németh, 2009; Hermann et al., 2014b). Although the relationship is rather complex between yield and SOM, using significant non-linear regression between SOM and yields of winter wheat, maize and alfalfa, saturation functions were given by Csathó (2003a; 2003b; 2003c) for the period of 1960 to 2000 based on long-term fertilizer experiments. Their results and saturation functions are in a good correspondence with the model-based findings of the current study.

Our scoring functions indicate the nutrient-response of crops and nutrient availability, as soil fertility is rather determined by nutrient dynamics (mobilization/mineralization-immobilization) and not nutrient concentrations (Kismányoky and Debreczeni, 2001; Debreczeniné and Németh, 2009).

The P scoring model illustrates that the same ammonium-lactate-soluble P_2O_5 content (AL-P) in a moderately acidic soil provides better nutrient supply for crops than is the case of alkaline and calcareous soils (Sarkadi et al., 1987; Hermann et al., 2014a). The models of the available K and Mg indicate that dynamics of these elements (adsorption, desorption and mass flow) is significantly influenced by soil texture and charge density on the surface of clay minerals (Buzás et al., 1979; Stout and Baker, 1981). In other words, identical ammonium-lactate-soluble K_2O and 1 M KCl-soluble Mg concentrations represent higher release rates and more readily available nutrient mineralization and mobilization in a sandy soil compared to clayey soil. Non-linear statistical relations between AL-soluble P and K contents and yields are also significant (Csathó 1997; 2003d; 2003e; 2003f).

As Mn availability is primarily determined by pH (Buzás et al., 1979; Gupta et al., 2008), this indicator was interpreted by taking into account the pH with a saturation model. Owing to its high adsorption capacity to the surface of clay minerals (Buzás et al., 1979; Gupta et al., 2008), Zn and Cu were interpreted as a function of soil texture. Nonetheless, Zn and Cu availability are also significantly influenced by other factors, including the presence of organic complexes and ion-antagonism mechanisms.

The majority of N and S is stored in organic compounds under the moderately arid climate of Hungary and are mineralized (mobilized) by microorganisms if their concentration decreases in soil solution (Tkaczyk et al., 2017). The mineralized N and S content and release rates are primarily influenced by soil water balance (precipitation and evaporation) and moisture regime of soils, therefore the linear interpretation of N and S was found sufficient for the current model („more is better"). However, the question may arise whether the most changeable mineralized N and S variables are adequate for a soil quality index? For almost all soil type, the means of scored N and S values were the lowest but it is highly unlikely that these indicators would be the most important limiting factors. These indicators rather show a momentary state in soils.

Our goal was to indicate the relative values of the interpreted indicators and show their impacts on soil properties. However, the simple addition of scores commonly gives a misleading result and contradicts the findings of the former Hungarian land evaluation studies (Géczy, 1969; Debreczeniné et al., 2003; Makó et al., 2007). Since the productivity of the soil is generated by the complex interaction of the simple soil properties, therefore, the combined analysis of indicators is crucial for the assessment of soil quality (Juhos et al., 2015). For example, some unfavourable properties can be compensated by other parameters, but in addition to synergies, antagonisms may also occur. Therefore weighting is usually indispensable.

5. Conclusions

Instead of the separate interpretation of soil indicators, their inter-correlations should be taken into account. Various soil physical and chemical properties must be incorporated as the nutrient availability of the soil is also affected by other soil properties. Soil moisture regime is also a more complex parameter and it is difficult to express using one simple indicator.

During the development of a soil quality index, the number of variables should be reduced relying on the outcomes of the multivariate statistical analyses (principal component analysis and discriminant analysis) of the total data base. However, the selection of the minimum dataset should not be exclusively based on these findings. Although individual PCs (PC3 and PC4) have a little impact on soil quality (for a given soil type), still, based on statistical analyses, they could be important indicators for e.g.: another soil type, or more specifically, could significantly impact soil physical and chemical properties from an agricultural viewpoint, like the availability of Zn and P. In the case of the Hungarian indicators and arable lands, we suggest to look at the variance and existing combinations of the interpreted scores and to rank the limiting factors according to the scores for each soil type.

In the current paper, however, our major objective was the identification of limiting factors for plant growth on the studied soil types. The most common limiting factors after their non-linear interpretation are texture, depth of groundwater table, SOM, pH, Na, available K, P and Zn which would be a minimum data set for a soil quality assessment. However, soil properties do not influence fertility and soil productivity independently, but rather in a complex and combined manner. When a land suitability index is based on these scores, the simple additive method for integration insufficient. In order to further advance a soil quality assessment model and improve the methodology of soil quality index development, our following goals target the determination the hierarchical ranking and grouping of soil parameters in a combined manner. For the given specific soil types the combination of these limiting factors should be studied and their weights need to be determined.

Acknowledgement: Supported by the ÚNKP-17-4-I and ÚNKP-18-4 New National Excellence Program of the Ministry of Human Capacities and Bolyai János Research Scholarship of the Hungarian Academy of Sciences (B. Madarász).

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Figure

Figures

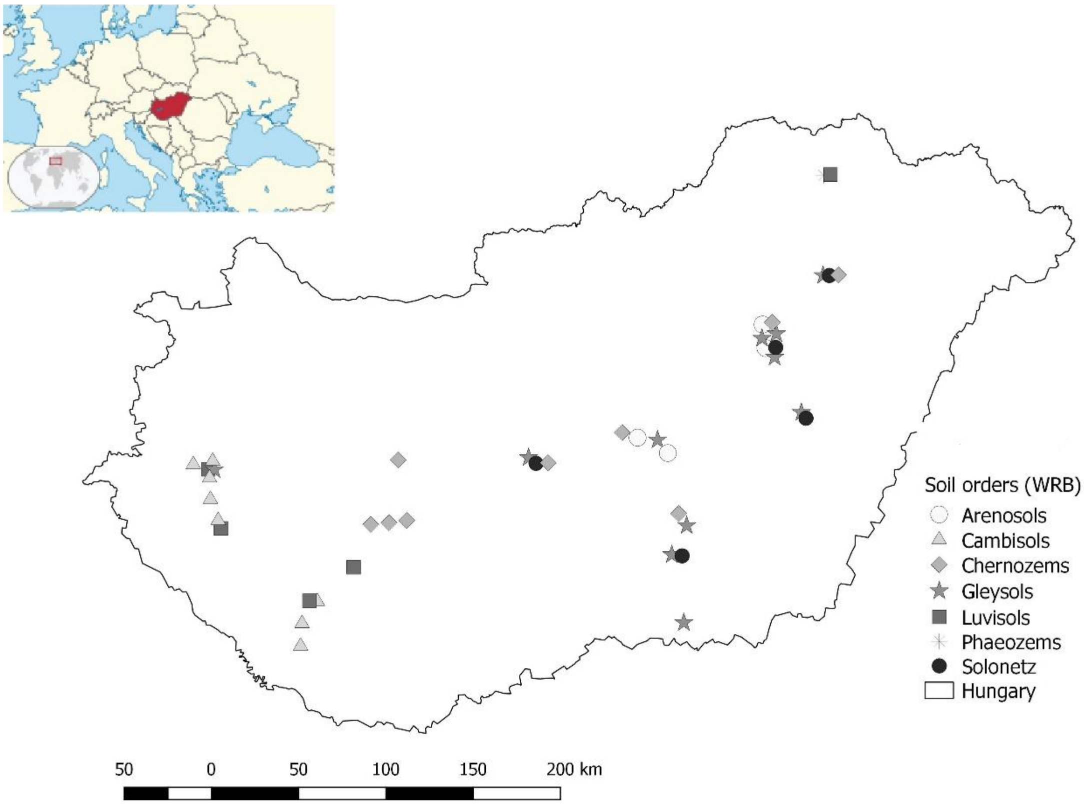


Fig 1 The geographical location of the sampling sites.

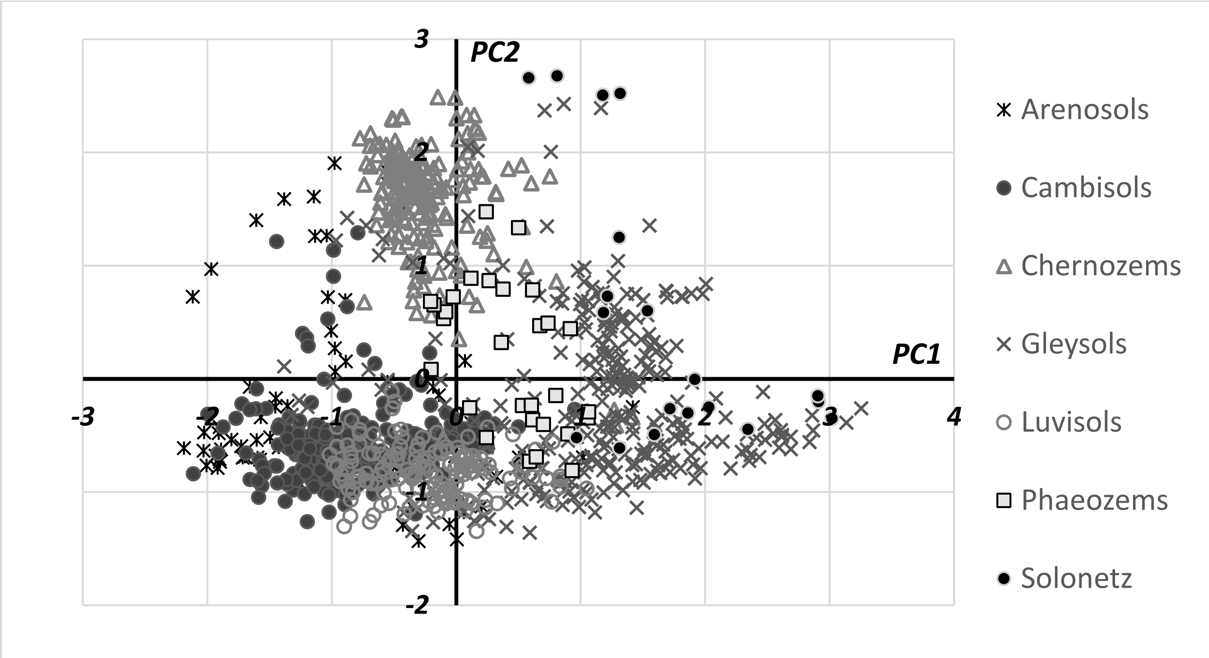


Fig 2 The first and second principal components (PCs) of soil orders.

Soil types primarily differentiated as a function of PC1 and PC2 values indicating the amount of mineral and organic colloids, and consequently, the cation adsorption capacity of the soil (PC1) and the acidity and alkalinity (PC2). The results of the discriminant analysis pointed out the common prediction power of the texture, SOM, K, Mg, Na, Cu, EC, CCE, pH and Mn by soil genetic types and the active soil forming processes.

Tables

Table 1

The soil types of the research sites and their qualifiers according to the World Reference Base (FAO, 2014) classification

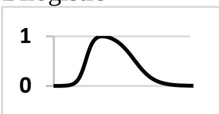
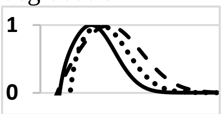
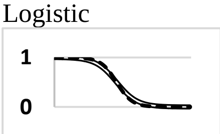
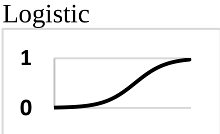
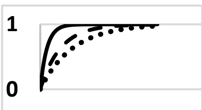
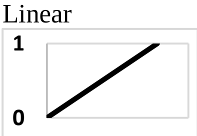
No.	Order	Principal qualifiers	Supplementary qualifiers	Depth of groundwater table (cm)	Number of samples
1	CHERNOZEMS	Calcic	Loamic/Siltic, Cambic	>500	178
2	CHERNOZEMS	Endogleyic, Calcic/Endocalcic	Loamic/Siltic	250-300	11
3	CHERNOZEMS	Calcic	Loamic/Siltic, Endosalic, Endosodic	300	8
4	PHAEOZEMS	Endocalcic, Cambic, Calcaric	Loamic	>500	29
5	CAMBISOLS	Endocalcaric, Eutric	Loamic/ Siltic	>800	91
6	LUVISOLS	Haplic	Loamic/Siltic	>800	164
7	GLEYSOLS	Mollic, Reductigleyic, Dystric (Eutric)	Clayic, (Endosodic)	80-120	73
8	GLEYSOLS	Mollic, Reductigleyic, (Endocalcaric), Eutric	Clayic, (Endosodic)	60-120	63
9	GLEYSOLS	Mollic, Fluvic, Reductigleyic, Dystric (Eutric)	Siltic/Arenic	50-120	16
10	GLEYSOLS	Mollic, Reductigleyic, (Endocalcaric), Eutric	Loamic	80-120	21
11	GLEYSOLS	Mollic, Reductigleyic, Dystric (Eutric)	Loamic	80-110	17
12	GLEYSOLS	Mollic, Oxigleyic, Dytric	Clayic	150-170	11
13	GLEYSOLS	Mollic, Oxigleyic, (Endocalcaric), Eutric	Loamic/Siltic	130-150	13
14	GLEYSOLS	Mollic, Oxigleyic, Dystric	Loamic/Siltic	150-180	16
15	GLEYSOLS	Mollic, Oxigleyic, Calcaric/Endocalcaric, Eutric	Clayic/(Loamic), Endosodic	140-150	16
16	GLEYSOLS	Mollic, Oxigleyic, Dystric	Clayic/Loamic, Endosodic	140-160	16
17	CAMBISOLS	Eutric, (Calcaric)	Arenic	>800	65
18	CAMBISOLS	Dystric/(Eutric)	Arenic	>800	103
19	ARENOSOLS	Fluvic, Calcaric/endocalcaric, Eutric	(Aeolic)	>200	35
20	ARENOSOLS	Fluvic, Dystric	-	>250	34
21	SOLONETZ	Endogleyic, Endosalic, Calcic	Loamic	200-250	7
22	SOLONETZ	Endogleyic, Endosalic (Endocalcic)	Clayic/Loamic	200-250	12
23	GLEYSOLS	Oxygleyic, Mollic, Dystric	Clayic /(Loamic), Endosalic, Sodic	150-170	30
24	GLEYSOLS	Oxygleyic, Mollic, Endocalcic/(Calcic), Eutric	Clayic /(Loamic), Endosalic, Sodic	150-170	10
25	GLEYSOLS	Oxygleyic, Fluvic, (Endocalcic), Eutric/Dystric	Siltic, Endosalic, Sodic	150	7

Table 2

References used for the indicator scoring and mathematical modelling

Soil quality indicator	Hungarian fertilization and soil long-term experiments; land evaluation methods
pH (CCE)	Géczy, 1968; Ángyán et al., 1982; Csathó, 2001; Debreczeniné and Németh, 2009; Nagy, 2011
Texture (depth of groundwater table)	Géczy, 1968; Várallyay, 2008; Makó et al., 2003; Rajkai et al., 2004; Farkas et al., 2005; Tóth et al., 2007b; Tóth et al., 2014; Rajkai et al., 2015
EC	Prettenhoffer, 1969; Szabolcs, 1971
SOM	Buzás et al., 1979; Csathó, 2003a; 2003b; 2003c; Debreczeniné and Németh, 2009; Hermann et al., 2014b;
P	Sarkadi et al., 1987; Csathó, 2003d; 2003e; 2003f; Hermann et al., 2014a
K	Buzás et al., 1979; Csathó, 1997
Mg	Buzás et al., 1979
Na	Prettenhoffer, 1969; Szabolcs, 1971
Zn	Buzás et al., 1979
Cu	Buzás et al., 1979
Mn	Buzás et al., 1979
S	Buzás et al., 1979; Debreczeniné and Németh, 2009
N	Buzás et al., 1979; Debreczeniné and Németh, 2009

Table 3 Scoring functions of soil quality indicators

Dependent variables	Models	Formula parameters depending on soil properties	p0	p1	p2	p3	p4
y_pH	Bilogistic  y=p0/(1+exp(-p1*(x-p2)))-p1/(1+exp(-p3*(x-p4)))	-	1.085	1.470	4.416	2.906	7.992
y_texture	Asym. saturation and degradation  y=(1-exp(-p1*(x-p3)))-(1-exp(-p2*(x-p4)^2))	**groundwater t. depth**					
		<85 cm		0.099	0.001	19.760	24.648
		85-120 cm		0.200	0.002	17.681	34.407
		120-180 cm		0.200	0.001	18.243	39.429
		>180 cm		0.169	0.001	17.661	43.765
y_EC	Logistic  y=p0+(p1-p0)/(1+exp(-p2*(x-p3)))	-	1.150	0.000	3.942	0.784	
y_Na		-	1.106	0.092	0.015	173.216	
y_P	Logistic  y=p0+(p1-p0)/(1+exp(-p2*(x-p3)))	**CCE**					
		<0.1 m/m%	0.000	1.000	0.034	66.649	
		0.1-1 m/m%	0.000	1.007	0.031	85.049	
		1.1-5 m/m%	0.000	1.002	0.029	108.089	
		5.1-10 m/m%	0.000	0.995	0.026	126.954	
		>10 m/m%	0.000	0.984	0.024	153.817	
y_K		**Soil texture**					
		sand	0.000	1.017	0.041	90.469	
		sandy loam	0.000	1.018	0.038	124.185	
		loam, s.loam	0.000	1.040	0.037	151.272	
		c.loam, s.clay	0.000	1.016	0.040	161.541	
		clay	0.000	1.011	0.041	171.385	
y_SOM	Saturation  y=p1*(1-exp(-p2*x))	sand		1.039	1.179		
		s. loam		1.087	0.770		
		loam, s. loam		1.199	0.454		
		c.loam, s.clay		1.978	0.167		
		clay		4.124	0.060		
y_Mg		sand		1.032	0.035		
		s.loam, loam, s.loam		1.074	0.018		
		c.loam, s.clay, clay		1.215	0.009		
y_Zn		sand, s. loam		1.016	1.646		
		loam, s.loam, c.loam, s.clay		1.298	0.408		
		clay		2.639	0.120		
y_Cu		sand, s.loam		1.013	6.002		
		loam, s.loam, c.loam, s.clay		1.075	2.278		
		clay		2.632	0.345		
y_Mn		**Soil pH**					
		pH<6		1.090	0.031		
		pH 6-8		1.031	0.139		
		pH>8		1.000	5.867		
y_N	Linear  $y=x/x_{max}$	-					
y_S		-					

The parameters are valid for $0 \leq y \leq 1$

Table 4

Descriptive statistics including mean, standard deviation (SD), kurtosis, skewness, and minimum and maximum values for measured soil indicators of the research sites (n=1046).

Parameter	Dimension	Min	Max	Mean	SD	Skewness	Kurtosis
pH	-	3.65	7.80	6.08	1.11	-0.066	-1.269
Texture*	cm^3 100 g^{-1}	25	71	39.24	9.79	0.682	0.071
EC	dS cm^{-1}	0.04	0.80	0.14	0.11	1.653	2.763
CCE	m/m % $CaCO_3$	0.00	30.00	1.92	3.88	2.796	10.060
SOM	m/m %	0.32	5.16	1.89	0.77	0.578	0.146
P	mg kg^{-1} P_2O_5	12	1980	154	171	4.824	33.534
K	mg kg^{-1} K_2O	40	1190	241	143	1.945	5.774
Mg	mg kg^{-1} MgO	18	1360	348	270	1.151	0.377
Na	mg kg^{-1} Na	1.00	751.00	36.50	52.94	5.485	48.097
Zn	mg kg^{-1} Zn	0.10	10.20	1.39	0.95	3.641	20.645
Cu	mg kg^{-1} Cu	0.36	21.70	4.08	3.45	1.898	4.042
Mn	mg kg^{-1} Mn	11.00	598.00	175.76	126.69	1.044	0.978
S	mg kg^{-1} SO_4-S	0.90	89.00	7.27	10.93	4.318	20.155
N	mg kg^{-1} NO_2+NO_3-N	0.00	78.13	9.76	8.79	2.671	10.107

* Soil texture was characterized by the water volume (cm^3) for consistency change to fluid for 100 g of soil. This water volume highly correlates with the particle size distribution. The values can be interpreted as follows: <25 – coarse sand, 25-30 – fine sand, 31-37 – sandy loam, 38-42 – loam and silty loam, 42-50 – clay loam and silty clay, >51 – clay texture.

Table 5

The Pearson correlation coefficients (r) matrix of the measured soil indicators.

	pH	Text.	EC	CCE	SOM	N	P	K	Mg	Na	Zn	Cu	Mn	S
pH	1													
Text.	-0.01	1												
EC	-0.12**	0.71**	1											
CCE	0.64**	0.00	-0.190**	1										
SOM	0.35**	0.60**	0.31**	0.43**	1									
N	-0.12**	0.21**	0.42**	-0.03	0.07*	1								
P	0.30**	-0.06*	0.00	0.17**	0.11**	-0.01	1							
K	0.15**	0.42**	0.45**	0.03	0.47**	0.19**	0.46**	1						
Mg	-0.24**	0.80**	0.68**	-0.26**	0.36**	0.15**	-0.12**	0.39**	1					
Na	0.01	0.32**	0.40**	0.17**	0.23**	0.27**	0.01	0.26**	0.41**	1				
Zn	-0.10**	0.16**	0.16**	-0.14**	0.20**	0.16**	0.36**	0.35**	0.18**	0.09**	1			
Cu	-0.33**	0.71**	0.68**	-0.29**	0.30**	0.32**	-0.04	0.38**	0.75**	0.40**	0.35**	1		
Mn	-0.34**	-0.10**	0.02	-0.50**	-0.26**	0.14**	-0.04	0.19**	0.10**	-0.02	0.30**	0.10**	1	
S	-0.19**	0.32**	0.48**	-0.06	0.14**	0.53**	-0.04	0.17**	0.26**	0.41**	0.12**	0.55**	-0.08*	1

**. Correlation is significant at the 0.01 level

*. Correlation is significant at the 0.05 level

Table 6

Results of the principal component analysis of soil indicators

Principal components	PC1	PC2	PC3	PC4
Eigenvalues	4.697	3.086	1.530	1.279
% of variance	33.550	22.044	10.931	9.134
Cumulated % of total variance	33.550	55.594	66.525	75.658
Indicators (communalities)	Factor loadings			
Texture (0.875)	**0.879**	0.128	-0.177	-0.234
Mg (0.871)	0.845	-0.198	-0.071	-0.336
Cu (0.835)	0.839	-0.321	0.080	-0.145
EC (0.668)	0.807	-0.098	-0.053	0.066
K (0.736)	**0.672**	0.241	0.460	-0.124
SOM (0.748)	0.645	0.543	-0.002	-0.191
Na (0.676)	**0.638**	0.305	-0.391	0.153
CCE (0.908)	-0.073	**0.943**	-0.117	0.014
Mn (0.766)	0.094	**-0.812**	0.298	-0.092
pH (0.742)	-0.073	0.812	0.223	-0.164
P (0.816)	0.023	0.445	**0.717**	0.321
Zn (0.627)	0.425	-0.163	**0.602**	0.239
S (0.733)	0.434	0.086	-0.289	**0.673**
N (0.588)	0.438	-0.178	-0.079	**0.601**

Boldface component-loadings are considered Minimum Data Set according to Andrews et al. (2004) (PCs have eigenvalues ≥1; highly weighted indicators have factor loading ≥0.40 and correlation coefficient between the indicators with highest loadings are <0.60)

Table 7

Descriptive statistics including mean, standard deviation (SD), kurtosis, skewness, and minimum and maximum values for interpreted soil indicators of the research sites (n=1046).

Parameter	Min	Max	Mean	SD	Skew	Kurt
y_pH	0,266	1,000	0,846	0,156	-1,038	0,547
y_texture	0,066	1,000	0,772	0,232	-1,067	-0,036
y_EC	0,557	1,000	0,995	0,024	-9,621	128,517
y_SOM	0,169	1,000	0,689	0,147	-0,100	-0,571
y_P	0,031	1,000	0,556	0,311	-0,015	-1,459
y_K	0,007	1,000	0,809	0,240	-1,202	0,396
y_Mg	0,478	1,000	0,982	0,058	-4,328	21,852
y_Na	0,049	1,000	0,961	0,123	-4,535	23,264
y_Zn	0,144	1,000	0,643	0,233	-0,147	-1,188
y_Cu	0,767	1,000	0,999	0,011	-16,054	299,033
y_Mn	0,478	1,000	0,991	0,049	-7,015	53,427
y_S	0,010	1,000	0,082	0,123	4,320	20,172
y_N	0,001	1,000	0,125	0,112	2,669	10,103

Table 8

The means of scored indicators by the soil types (the name of the soil types are given in *Table 1*)

	Soil classification																								
		CH		PH	CM	LV			Reductigleyic GL					Oxigleyic GL			CM (Arenic)		AR		SN			GL (Sodic)	
Scored indicators	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
y_pH	0,83	0,95	0,84	0,95	1,00	***0,79***	***0,77***	0,99	0,82	0,97	***0,68***	***0,76***	0,98	***0,73***	0,98	***0,69***	0,99	***0,75***	0,93	***0,69***	0,86	0,84	0,68	0,94	0,91
y_texture	0,95	0,97	0,94	0,97	0,92	0,92	**0,32**	**0,37**	0,85	0,85	0,82	0,82	0,98	0,96	0,81	0,92	0,61	**0,57**	0,68	***0,66***	0,97	0,95	0,81	0,86	0,93
y_EC	1,00	1,00	1,00	0,99	1,00	1,00	1,00	0,99	1,00	1,00	0,99	1,00	1,00	1,00	0,98	0,99	1,00	1,00	1,00	1,00	1,00	0,96	0,93	0,99	1,00
y_SOM	0,86	**0,75**	0,81	***0,63***	***0,62***	***0,65***	***0,62***	**0,55**	0,81	0,54	**0,58**	***0,67***	***0,77***	***0,78***	**0,53**	***0,61***	***0,75***	***0,71***	***0,76***	***0,61***	***0,71***	**0,55**	**0,53**	***0,63***	***0,78***
y_P	**0,42**	0,86	**0,51**	**0,58**	**0,39**	**0,56**	***0,61***	**0,53**	**0,57**	**0,52**	**0,26**	***0,77***	**0,50**	**0,29**	***0,64***	**0,49**	**0,57**	0,81	0,64	***0,64***	0,96	***0,67***	***0,69***	***0,68***	**0,38**
y_K	0,86	0,96	0,90	0,98	***0,72***	**0,65**	0,85	0,92	0,94	0,82	***0,69***	0,99	0,92	0,96	0,96	0,63	0,84	***0,75***	0,87	***0,64***	1,00	0,91	0,97	0,98	0,99
y_Mg	0,98	1,00	0,97	0,99	1,00	1,00	1,00	0,99	1,00	0,97	1,00	1,00	1,00	1,00	1,00	1,00	0,99	0,92	0,95	0,91	1,00	1,00	1,00	1,00	1,00
y_Na	0,99	0,99	0,92	1,00	1,00	1,00	0,98	0,99	0,99	0,99	1,00	0,99	0,99	0,97	0,86	0,85	1,00	1,00	0,99	1,00	**0,28**	**0,36**	***0,68***	***0,64***	**0,47**
y_Zn	**0,51**	***0,72***	***0,62***	***0,61***	***0,72***	***0,67***	**0,59**	**0,32**	***0,78***	**0,50**	**0,37**	***0,77***	***0,78***	***0,75***	**0,35**	**0,56**	0,87	0,82	0,87	***0,78***	***0,64***	***0,63***	**0,51**	**0,45**	0,91
y_Cu	1,00	0,99	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	0,98	1,00	1,00	1,00	1,00	1,00	1,00	0,99	0,99	1,00	1,00	1,00	1,00	1,00
y_Mn	1,00	1,00	1,00	1,00	1,00	1,00	0,94	1,00	0,99	1,00	0,99	1,00	1,00	1,00	1,00	1,00	1,00	0,99	1,00	0,92	1,00	1,00	1,00	1,00	1,00
y_S *	0,07	0,12	0,09	0,07	0,06	0,06	0,08	0,06	0,04	0,05	0,03	0,15	0,07	0,05	0,08	0,28	0,04	0,05	0,05	0,05	0,08	0,34	0,57	0,06	0,04
y_N *	0,08	0,29	0,16	0,19	0,10	0,13	0,11	0,11	0,06	0,11	0,12	0,21	0,11	0,17	0,12	0,22	0,12	0,10	0,11	0,15	0,28	0,20	0,40	0,17	0,08

Normal scores: y=0.81-1.00 No to Slight limitation; ***Bold-italic scores*** y=0.61-0.80 Moderate limitation; **Boldface scores:** strong limitation y=0.41-0.60; **Underlined boldface scores**: y≤0.40 not suitable for crops

* Low means due to the large scale and skewness

Table 9

The most common indicator scoring functions in the literature

Soil quality indicator	bell-shaped curve ('mid-point optimum')	non-linear sigmoid curve	linear function
pH	Rahmanipour et al., 2014; Mukherje and Lal, 2014; Sharma et al., 2014		
Texture, clay content	Armenise et al., 2013; Vasu et al., 2016		„more is better“ Masto et al., 2015
depth of groundwater table and relative topography			„less is better“ or „more is better“ Zhang et al., 2004; Yao et al., 2014; Zobeck et al., 2014; Jamil et al. 2017
EC and SAR „less is better“		Andrews et al., 2004; Rahmanipour et al., 2014; Nabiollahi et al., 2017	Liebig et al., 2001; Raiesi, 2017; Vasu et al., 2016
SOM "more is better"		Li et al., 2013; Yao et al., 2014; Ivezic et al., 2015; Thomazini et al., 2015; Raiesi, 2017	Mukherje and Lal, 2014; Sharma et al., 2014; Singh et al., 2014; Nakajima et al. 2015; Raiesi, 2017; Ramachandran et al. 2016; Vasu et al. 2016; Biswas et al. 2017; Nabiollahi et al. 2017
available P "more is better"		Armenise et al., 2013; Li et al., 2013; Ivezic et al., 2015	Sharma et al., 2014, Singh et al., 2014; Ramachandran et al., 2016
available K "more is better"	Yao et al. 2014	Armenise et al. 2013; Li et al. 2013	Rahmanipour et al. 2014; Sharma et al. 2014; Singh et al. 2014
available Mg, Zn, Cu, Mn, S, N "more is better"	Lima et al., 2012	Andrews et al., 2004; Qi et al., 2009	Saglam et al., 2015; Sharma et al., 2014; Singh et al., 2014; Ramachandran et al., 2016; Biswas et al., 2017